Annex 4:
Proportion of urban residents and urban land less than 10 metres above sea level

Method in brief

This analysis, produced for the Coalition's *Climate Emergency, Urban Opportunity*[1] report, estimates the share of the population living in low-elevation coastal zones and thus exposed to coastal hazards – and the share of that population that is urban. The analysis was conducted by Deborah Balk (CUNY Institute for Demographic Research, City University of New York), Gordon McGranahan (The Institute of Development Studies), Kytt MacManus (Center for International Earth Science Information Network, Columbia University) and Hasim Engin (CUNY Institute for Demographic Research, City University of New York). The results presented in *Seizing the Urban Opportunity* and the six accompanying country reports are drawn directly from that analysis. However, since the methodology is reproduced here as it appeared in the original 2019 report, with only minimal edits, the selected results presented at the end are not specific to the six countries, but rather the same as were included in the original methodology.

Scope of analysis

The overall goal of this analysis was to update estimates of the population living at risk of coastal hazards, using the basic methodology established in McGranahan et al., 2007.[2] Expanding upon that research, here we also aim to make some additional distinctions in the understanding of differential risk and degrees of urbanisation.

Therefore, we distinguish between populations at high risk (living below 5 metres contiguous to coast) and those at medium risk (living at 5–10 metres contiguous to coast);[3] and we distinguish between dwellers of cities and other types of urban and quasi-urban areas (such as peri-urban outlying areas and smaller towns). We also describe changes in the past 25 years, from 1990 to 2015.

Data

In the 10 years since the 2007 study, many new renderings of urban areas have become available. We have selected data from the Global Human Settlement Layer (GHSL) project suite produced by the Joint Research Centre (JRC) of the European Commission.[4] At its core are more than 40,000 Landsat scenes, which have been processed in a consistent manner across countries and over time using advanced machine learning algorithms. The data, GHS-BUILT described in Table A4.1, are binary, indicating either the presence or absence of a built structure in each 30-metre grid cell, and aggregated to 250 metres by the data producers at the JRC (see Florczyk et al., 2019) to represent the fraction of built-up land in each pixel. Data are available for four time periods (1975, 1990, 2000, and 2015), of which we used from 1990 to 2015 here. (We do not have population data at a spatial resolution that make analysis of 1975 meaningful.) This dataset has been cross-validated or analysed with census-designated classes of urbanisation in the recent studies of the U.S., and this process generally confirmed the accuracy of the GHSL algorithms, except perhaps in very sparsely settled rural regions.[5]

A second derived data product, GHS-SMOD, was used to construct a “degree of urbanisation” grid.[6] This modelled surface uses built-up area (GHS-BUILT) along with population data (GPW v4.11 input data reallocated) in the form of GHS-Pop (described momentarily) and a set of density and proximity criteria to classify population and land area into seven classes along a rural-to-urban continuum. This new data product has not yet been cross-validated in the peer-reviewed literature, but such studies are under way. We felt that it was important to use a refined measure of urban locations rather than a simple dichotomy for this study, but owing to the owing to the fact that rigorous validation has not yet been completed, we reduced the seven classes to three as indicated in Table A4.2. In broad strokes, these represent cities, other urban and quasi-urban locations (such as towns, peri-urban locations), and rural areas. We also used GRUMP, and simple built-up thresholds from GHS-BUILT, as a type of sensitivity analysis[7] on the urban classifications.

In an important departure from earlier studies,[8] the data used here to construct the low elevation coastal zone (LECZ) represent recent advances in the processing of the underlying data. The underlying data, from the Shuttle Radar Topography Mission (SRTM), have known vertical errors, whereby some low-lying vegetated areas are erroneously estimated—what is known as tree-height bias. Corrections to the SRTM have been made in a new database, the Multi-Error-Removed Improved-Terrain DEM (MERIT), and it is that dataset that is the basis of the LECZ exposure used here.[9] We used the original SRTM data for the sensitivity analysis.[10]

For population data, we used the GHS-Pop data as our primary data, and GPW v.4.11 (an earlier version of which was used in the original McGranahan et al. study[11]) for the sensitivity analysis. The GHS-Pop data apply the GPW v.4.11 inputs and reallocate population to GHS-BUILT areas. In this way, population from large, sparsely populated administrative units is moved towards the detected built-up area rather than being assumed to be evenly distributed throughout the entire polygon.

Since the population data and the urban extent data both use GHS-BUILT to reallocate population and then classify those areas in varying degrees of urban, they are internally consistent. For this reason, we used these as our basic data product for the production new estimates of populations at risk in the LECZ along an urban continuum. These internally consistent data, however, may tend to somewhat over-concentrate population into areas that are obviously built-up, leading to somewhat more urban residents. Because GHSL is not as expansive as the night-time lights used in the 2007 study[12] (which were very inclusive of core urban areas and their surrounding areas), we used a newer class of estimates of urban land than in the initial study; these data tend to produce smaller “core” urban centres but also a wider range of the full urban continuum.

Table A4.1. Data Sources[13]

Theme	Dataset	Abbreviation	Spatial resolution	Reference
Elevation	Shuttle Radar Topography Mission elevation data	SRTM	90m	ISciences, 2003[14]
	Multi-Error-Removed Improved-Terrain DEM	MERIT	90m	Yamazaki et al., 2017[15]
Urban rural classifications	Global Human Settlement – Settlement "degree of urbanisation" Model Grid	GHS-SMOD	1km	Florczyk et al., 2019[16]
	Global Human Settlement – Built-up Grid	GHS-BUILT	300m	Pesaresi et al., 2015[17]
	Global Rural Urban Mapping Project	GRUMP	1km	CIESIN et al., 2017[18]
Population	Global Human Settlement – Population Grid	GHS-Pop	300m	JRC and CIESIN, 2018[19]
	Gridded Population of the World, v.4.11	GPW v.4.11	1km	CIESIN, 2018[20]

Table A4.2. Urban classifications according to GHS-SMOD Data

Code	Short formal description	Intuitive description	Formalisation
RUR	Rural grid cells	Rural areas	xpop[21] <300 OR ∑xpop(4-conn cluster[22] of xpop >300) <5000
LDC	Urban clusters	Towns or suburbs	xpop >300 AND ∑xpop(4-conn cluster) >5000, no generalisation step, AND not "urban centres"
HDC	Urban centres	Cities	{xpop >1500 OR xbu[23]>0.5 } AND ∑xpop(4-conn cluster) >50000, followed by generalisation step: single cluster, iterative 3x3 kernel union-majority filter until idempotence, filling gaps (holes) < 15 square km

Approach

We used the above layers to estimate “zonal statistics” as described above. Table A4.3 highlights the processing steps necessary to condition the data layers, make them compatible with one another, and overlay them in order to generate the estimates in Tables A4.4 and A4.5. This includes re-projecting spatial layers, aggregating finely resolved data to compatible resolutions, and so forth. The data were all re-projected into World Geodetic System 1984 (WGS84) and aggregated or resampled to 300 metres resolution to conform with GHS-POP inputs. The analysis was undertaken in ArcGIS, python and R.

Table A4.3. Summary of basic data processing steps

Data type/step	Processing decisions and steps
Elevation	
Aggregate MERIT-DEM	The MERIT-DEM elevation data were aggregated with a Majority Filter from approximately 100m to approximately 300m to conform with population and built-up inputs aggregated with a Majority Filter from approximately 100m to approximately 300m to conform with population and built-up inputs.
Create LECZ extracts	The aggregated MERIT-DEM data were extracted into 5m and 10m zones.
Population and built-up preprocessing	
Extract	GHS-POP was extracted by country and LECZ.
Extract and project	GHS-BUILT was extracted by country and LECZ, and projected from Mollweide into WGS84 to conform with the native projection of elevation data.
Resample and extract	GHS-SMOD, GPW v.4.11 and GRUMP were down-sampled to 300m and extracted by country and LECZ. GHS-SMOD was projected from Mollweide into WGS84 to conform with the native projection of elevation data.
Derivation of urban gradients	
Threshold GHS-BUILT	GHS-BUILT was transformed into two binary masks of Built-up/Not Built-up. The first mask assumed that any pixel greater than or equal to 1 pct Built-up was in the Built-up category. The second mask assumed that any pixel greater or equal to 50 pct Built-up was in the Built-up category.
Aggregate GHS-SMOD	GHS-SMOD was aggregated to produce two binary masks. The first mask combined SMOD into three classes: High Density Clusters (HDC), Low Density Clusters (LDC) and Rural Areas (RUR). The second mask combined SMOD into two classes: (HDC, LDC), and RUR, respectively.
Zonal statistics	
Calculation	More than 100,000 individual zonal statistics tables were produced for every combination of inputs, by country and LECZ.

Limitations

The elevation data was produced and distributed in the WGS84 Geographic Coordinate System. The data from GHSL, however, were produced and distributed in the Mollweide Equal Area Projected Coordinate System (not including GHS-POP, which is also released in a WGS84 version). In order to conduct analyses on these data sources it is necessary to harmonise their coordinate systems, but the projection of raster data is not without complications.

When a raster dataset is projected from one coordinate system to another, the registration and total number of pixels represented are altered. In other words, the number of pixels may change along with the location of those pixels relative to ground truth. We opted to maintain the projection of the elevation data source (WGS84) in order not to introduce uncertainties about the location of the LECZs. We therefore needed to project GHS-BUILT and GHS-SMOD to conform with the elevation source.

The thematic layers (GHS-BUILT, GHS-SMOD) were not simple to validate owing to the fact that there is no available alternative source for these data to compare with. We expect that any error introduced by projecting these data from Mollweide to WGS84 using a “nearest neighbour” approach is quite minimal; however, it should be noted that because of the fact that the LECZs represent small swathes of land area, they are also more sensitive to any apparent shifts of pixel locations. Although the projection issue does produce some uncertainty, it would not have been possible to use these data sources together without taking this approach.

Selected results

Table A4.4 presents selected results from the analysis to provide more detail about countries that might be of particular interest. Table A4.5 further identifies the population growth rate in specific low elevation coastal zones.

Table A4.4. Population and percent of national population in urban centres and quasi-urban clusters in the LECZ, 2015, for select countries

Country	Total population in urban centres in the 10m LECZ	% of country population in urban centres in the LECZ	Total population in quasi-urban clusters in the LECZ	% of country population in quasi-urban clusters in the LECZ
Indonesia	34,804,741	13.5%	12,596,966	4.9%
China	129,506,529	9.4%	52,128,053	3.8%
India	55,216,398	4.2%	15,611,043	1.2%
Mexico	2,916,240	2.3%	1,508,959	1.2%
Ghana	541,916	2.0%	643,626	2.3%
Tanzania	236,783	0.4%	104,160	0.2%

Table A4.5. Average annual growth rate of the urban centre, quasi-urban cluster, rural and total population in the LECZ globally, 2000–2015

Elevation	Total population growth rate	Urban centre population growth rate	Quasi-urban cluster population growth rate	Rural population growth rate
0–5 m	1.41%	2.26%	0.67%	0.54%
5–10m	1.24%	1.85%	0.23%	0.32%
0–10m	1.30%	1.98%	0.41%	0.42%
non-LECZ	1.13%	1.62%	0.68%	0.78%

Endnotes

[1] CUT, 2019, "Climate Emergency, Urban Opportunity."

[2] McGranahan, Balk, and Anderson, 2007, "The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones," *Environment and Urbanization*.

[3] According to Gesch, 2018, LECZs constructed on the DEMs using values below 5 metres in single increments produce high errors. For this reason, we construct two zones only. See Gesch, 2018, "Best Practices for Elevation-Based Assessments of Sea-Level Rise and Coastal Flooding Exposure," *Frontiers in Earth Science*.

[4] Florczyk et al., 2019, "GHS Urban Centre Database 2015, Multitemporal and Multidimensional Attributes - European Union Open Data Portal"; Pesaresi et al., 2015, "GHS-BUILT R2015B - GHS Built-up Grid, Derived from Landsat, Multitemporal (1975, 1990, 2000, 2014)."

[5] D. Balk et al., 2018, "Understanding Urbanization: A Study of Census and Satellite-Derived Urban Classes in the United States, 1990-2010," *PLOS ONE*.

[6] Florczyk et al., 2019, "GHS Urban Centre Database 2015, Multitemporal and Multidimensional Attributes - European Union Open Data Portal."

[7] The sensitivity analysis compared estimated populations (or urban class, or elevation) by varying input data sets in order to see the impacts of data choice on the final results. (These are not accuracy assessments, because any set of input data might have their own associated inaccuracies.

[8] McGranahan, Balk, and Anderson, 2007, "The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones," *Environment and Urbanization*; CIESIN, 2013, "Low Elevation Coastal Zone (LECZ) Urban-Rural Population and Land Area Estimates, Version 2."

[9] Yamazaki et al., 2017, "A High-Accuracy Map of Global Terrain Elevations," *Geophysical Research Letters*.

[10] ISciences, 2003, "SRTM30 Enhanced Global Map – Elevation/Slope/Aspect."

[11] McGranahan, Balk, and Anderson, 2007, "The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones," *Environment and Urbanization*.

[12] Night-time lights are known to have a "blooming" quality which leads to apparently larger settled areas. Therefore, urban areas tend to include surrounding settlements as well.

[13] Note: Grey background refers to data used in sensitivity analysis only.

[14] ISciences, 2003, "SRTM30 Enhanced Global Map – Elevation/Slope/Aspect."

[15] Yamazaki et al., 2017, "A High-Accuracy Map of Global Terrain Elevations," *Geophysical Research Letters*.

[16] Florczyk et al., 2019, "GHS Urban Centre Database 2015, Multitemporal and Multidimensional Attributes - European Union Open Data Portal."

[17] Pesaresi et al., 2015, "GHS-BUILT R2015B - GHS Built-up Grid, Derived from Landsat, Multitemporal (1975, 1990, 2000, 2014)."

[18] CIESIN et al., 2017, "Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Urban Extent Polygons, Revision 01"; see also D. L. Balk et al., 2006, "Determining Global Population Distribution: Methods, Applications and Data," in *Advances in Parasitology*.

[19] JRC and CIESIN, 2018, "GHS Population Grid, Derived from GPW4, Multitemporal (1975, 1990, 2000, 2015) - European Union Open Data Portal."

[20] CIESIN, 2018, "Gridded Population of the World, Version 4 (GPWv4): Population Count Adjusted to Match 2015 Revision of UN WPP Country Totals, Revision 11."

[21] Population density thresholds used for each GHS-SMOD Class.

[22] Group of 4 pixels connected. Rook's move connections.

[23] Built up density thresholds used for each GHS-SMOD.

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